A Few AI Challenges Raised while Developing an Architecture for Human-Robot Cooperative Task Achievement

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Over the last five years, and while developing an architecture for autonomous service robots in human environments, we have identified several key decisional issues that are to be tackled for a cognitive robot to share space and tasks with a human. We introduce some of them here: situation assessment and mutual modelling, management and exploitation of each agent (human and robot) knowledge in separate cognitive models, natural multi-modal communication, "human-aware" task planning, and human and robot interleaved plan achievement.

As a general "take home" message, it appears that *explicit* knowledge management, both symbolic and geometric, proves to be a successful key while attempting to address these challenges, as it pushes for a different, more semantic way to address the decision-making issue in human-robot interactions.

This abstract summarizes the main ideas of a full article submitted to the special issue on Robotics of the Artificial Intelligence Journal.

One Architecture, Many Cognitive Skills Building a service robot for autonomous human-robot interaction involves many components that translate cognitive skills into softwares. Connecting these multiple independent software modules in one coherent robotic architecture is a first challenge that goes beyond simple engineering: dealing with the intricate semantics of human-level interaction has to be properly addressed. We have been researching to this end a robotic architecture focused on explicit knowledge representation and manipulation (at the deliberative level): components' "APIs" become "ASIs": *application* semantic *interface*, as first-order-logic statements act as *lingua franca* between the components.

Figure 1 gives an overview of our architecture. An active knowledge base (Oro (Lemaignan et al. 2010)), conveniently thought as a *semantic blackboard*, connects most of the modules together: the *geometric reasoning* module (Spark) produces symbolic assertions (like ⟨ `BOOK1 isOn TABLE`⟩) describing the state and dynamics of the robot's environment. These logical statements are stored in the knowledge base, and queried back by the language processing module (Dialogs), the symbolic task planner (HATP) and the execution controller. The output of the language processing module and the activities started by the robot controller are likewise stored as symbolic statements.

For instance, when processing a sentence like "give me another book", the Dialogs module queries the knowledge base: `find(?book type Book, ?book differentFrom BOOK1)`, and write back assertions like ⟨ `HUMAN desires GIVE_ACTION45, GIVE_ACTION45 actsOn BOOK2`⟩. The HATP planner then uses the knowledge base to initialise the planning domains with similar requests (`find(BOOK2 isAt ?location)`, etc.), and the execution controller typically monitor conditions (by subscribing to events like: `onNewMatch(HUMAN desires ?goal)`) and stores what the robot is currently doing (⟨ `myself currentlyPerforms GIVE_ACTION45`⟩).

As we already see in this example, our software modules can be seen as **translators** from *human* cognitive skills to *robotic* cognitive skills. In our context, we call *cognitive skills* the **deliberative behaviours** that are 1. **stateful** (keeping track of previous states is typically required for the component to perform adequately), 2. **amodal** in that the skill is not inherently bound to a specific perception or actuation modality, 3. manipulate **explicit and grounded semantics**, typically by the mean of symbolic reasoning, 4. operate at the **human-level**, *i.e.* are legible to the humans, typically by acting at similar levels of abstraction.

Even before discussing the AI challenges specifically raised by each of the skills we want to endow our robot with, this definition of a *cognitive skill* already hints at a range of general AI questions like: What *amodal* actually means for an "embodied Turing machine"? Is conveying *human-level semantics* achievable by the mean of symbolic reasoning? Should we at all try to *translate* human skills to robotic skills? Still, we can outline the main cognitive tools that we have researched, and how they question artificial intelligence in their own manner.

From Cognitive Skills to AI Challenges We distinguish between what we call *intrinsic* and *extrinsic*

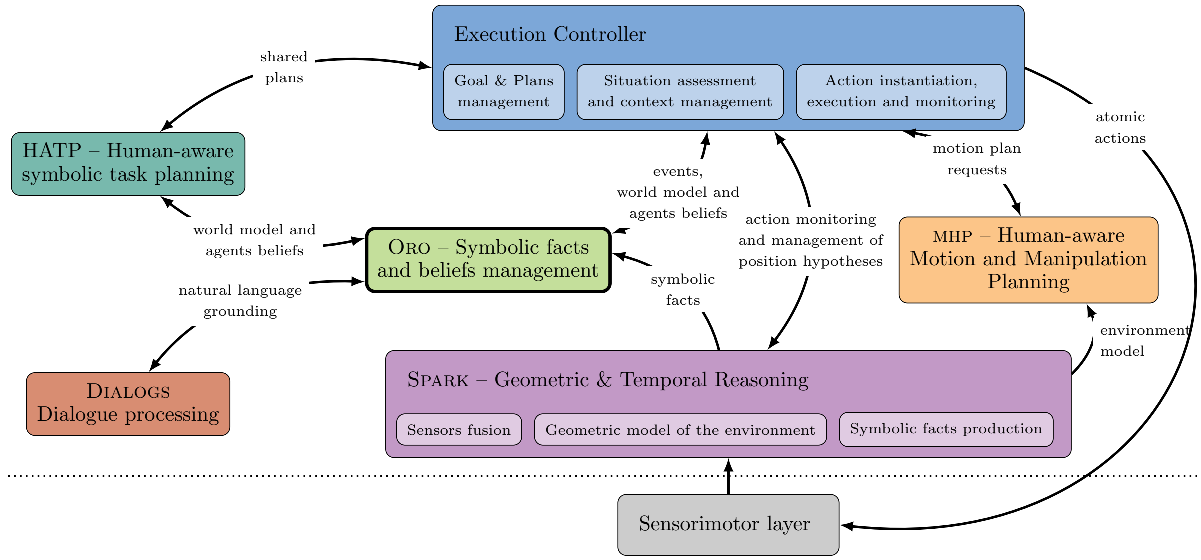

Figure 1: A deliberative architecture for autonomous service robots.

cognitive capabilities: *intrinsic* are those skills that are tightly bound to the knowledge model (and hence implemented close to the knowledge base). In our system, they include for instance **symbolic reasoning** and **mutual modelling**. *Extrinsic* cognitive skills, on the other hand, are partially decoupled from the central knowledge base (they can usually work – with reduced functionalities – without any). We have investigated **human-aware situation assessment**, **natural language grounding**, **social task planning** and **high-level execution control**. We introduce below four of these skills, and relate them to the underlying AI challenges they raise (and attempt to partially address).

We manage symbolic knowledge in our architecture via the Oro (Lemaignan et al. 2010) knowledge base, that relies on standard tools: Description Logics (OWL) as first-order-logic formalism and the Pellet open-source reasoner. This provides the whole system with standard inference capabilities like *consistency checking*, *concept satisfiability*, *classification* and *realisation*.

Many alternatives to description logics exist and have also been investigated in robotics (*modal logic*, *temporal logic*, different kind of *probabilistic logics*, specialized approaches like *Answer Set Programming*, etc.), and a synthesis on logic formalisms that would address the specific needs of HRI (beyond the *expressiveness vs. tractability* trade-off) would certainly be a welcome contribution.

We also conducted research on *mutual modelling* through the implementation of a simple theory of mind (the cognitive ability that allows a subject to represent the mental state of another agent). From a robotics point of view, it supposes the ability to build, store and retrieve separate models of the beliefs of the agents the robot interacts with. Our knowledge base implements such a mechanism by the mean of independent ontologies for each agent the robot interacts with, and maintain then different (and possibly diverging) knowledge models based on visual perspective taking (Sisbot, Ros, and Alami 2011).

While this approach enabled us to reproduce the classical *False-Belief* experiment (Warnier et al. 2012), it is also clear that *mutual modelling* covers more than what *visual* perspective taking provides to the system, and more research is required to actually take into account what the human knows about the robot (and vice versa) regarding expected knowledge, skills, plans, emotions, etc. This line of research would support an interdisciplinary approach, where AI would have to discuss with the other fields of cognitive sciences.

Natural language understanding is another classical AI challenge that we have investigated (Lemaignan et al. 2011), focusing on the *grounding* (Coradeschi and Saffiotti 2003) issue: how to establish a common ground between the robot and the human, relying on the different communication modalities elicited by the robot. We found that representing the robot's belief state with human-level semantics simplifies dialogue understanding, both in terms of grounding (because the robot already represents what it perceives at a level of abstraction that is close to the human one) and of interpretation (the robot's planner takes as input task descriptions that are also close to what the human expresses). Much remains however to be done, starting with better speech *recognition* (which likely asks for a better integration with speech *understanding*).

Finally, human-aware task planning is a cognitive capability of interest for both the AI and HRI communities: we have developed an original task planner, HATP (Lallement, De Silva, and Alami 2014), that augments the standard HTN approach by allowing the system to generate interleaved plans for multiple agents, so-called *shared plans*. These are then used to anticipate human action or to propose to human to act. A set of *social rules* together with cost-based plan selection allows to promote the (shared) plans that suit better human preferences and needs or to tune the workload balance between participants, the human or the robot, depending on the context.

A fruitful cooperation Human-Robot Interaction is definitely an area full of challenges for Artificial Intelligence. We have briefly outlined here a few challenges that we attempt to address in our architecture: indeed, besides all "standard" robotic challenges in terms of autonomy, it is interesting to identify and investigate issues dealing with "human-aware" planning and reasoning.

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